

Orange is an open source visualization and analysis tool. Data mining is done through visual programming or python scripting.

KNIME(Konstanz Information Miner) is open source data analytics, reporting platform. It integrates various components through its modular data pipelining concept.

NLTK is a leading platform for building Python programs to work with human languages data.

Rattle GUI is a free and open source software provides a graphical user interface for data mining using R statistical programming languages. Rattle allows dataset to be partitioned into training, validation, and testing.

Among all these tools static analysis uses taint analysis which is a tool of it in this project. Also data mining make use of AST which is tool of data mining. WAP does not use data mining to identify vulnerabilities but to predict whether the vulnerabilities found are really vulnerabilities or not.

There are some classifiers which are being used to categorize the vulnerabilities into classes. The classifiers are Logistic regression, Linear Regression, Decision trees, Perceptron, ID3,C4.5/J48,Random Tree, Random Forest, K-NN, Naïve Bayes, Bayes Net, MLP, SVM, etc.

Logistic regression is regression model where dependant variable is categorical. Cases where output occurs in 2 values like, “0” or “1”, “yes” or “no” etc.

Linear regression is approach for modeling the relationship between various kind of variables.

Decision tree is a decision support tool that uses a tree like graph or model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility.

Perceptron is an algorithm for supervised learning of classifiers whose output is in 2 forms.

ID3 is metadata container most often used in conjunction with MP3 audio file format.

Random tree is a tree that is formed by stochastic process. Types of this random trees include uniform spanning tree, Random minimal spanning tree, Random binary tree, random recursive tree etc.

Random forest are an ensemble learning method for classification, regression and other tasks, that operate by construction a multitude of decision trees at training time and outputting the class that is mode of classes.

K-NN is a non-parametric method used for classification and regression.

Naïve Bayes classifiers requires a number of parameters linear in the number of variables in learning problem.

Bayes Net is a probabilistic graphical model that represents a set of variables along with their conditional dependencies via a directed acyclic graph.

Among all these classifiers mentioned only 3 best classifiers are selected based on attribute dependency.

Some Induction Rule classifiers are again used to find the correlation between the vulnerabilities found and an attributes collected from them. These classifiers include PRISM, PART, JRip, Ridor etc.

PRISM takes an input a training set entered as a file of ordered set of attributes and classifies input from separate file at start of program and results are output as an individual rules.

PART produces a set of rules called decision list which are ordered set of rules. A new data is compared with each rule in list and item is assigned a category of first matching rule.

Ridor generates default rule first and then exceptions for the default rule with least error rate. Then it generates the “best” exceptions for each exception and iterates until pure.

JRip class implements a propositional rule learner, repeated Incremental Pruning to produce Error Reduction.

4. Conclusion

In this paper we present the techniques for securing web application vulnerabilities. The techniques make use of 2 tools static analysis and data mining which are most effective methods and provides results faster and correct manner.

REFERENCES

1. Symantec, "Internet threat report. 2012 trends, vol. 18," Apr. 2013.
2. W. Halfond, A. Orso, and P. Manolios, "WASP: protecting web applications using positive tainting" IEEE Trans.
3. Softw. Eng., vol. 34, no. 1, pp. 65–81, 2008.
4. T. Pietraszek and C. V. Berghe, "Defending against injection attacks through context-sensitive string evaluation," in Proc. 8th Int. Conf. Recent Advances in Intrusion Detection, 2005, pp. 124–145.
5. X. Wang, C. Pan, P. Liu, and S. Zhu, "SigFree: A signature-free buffer overflow attack blocker," in Proc. 15th USENIX Security Symp., Aug. 2006, pp. 225–240.
6. J. Antunes, N. F. Neves, M. Correia, P. Verissimo, and R. Neves, "Vulnerability removal with attack injection," IEEE Trans. Softw. Eng. vol. 36, no. 3, pp. 357–370, 2010.
7. R. Banabic and G. Candea, "Fast black-box testing of system recovery code," Proc. 7th ACM European Conf. Computer Systems, 2012, pp. 281–294.
8. Huang, Yao-Wen et al, "Web application securit by fault injection and behavior monitoring," Proc. 12th Int. Conf. World Wide Web, 2003, pp. 148–159.
9. Huang, Yao-Wen et al, "Securing web application code by static analysis tools and runtime protection," Proc. 13th Int. Conf. World Wide Web, 2004.,
10. N. Jovanovic, C. Kruegel, and E. Kirda, "Security using alias analysis for static removal of web application vulnerabilities," in Proc. 2006 Workshop on Programming Languages and Analysis for Security, Jun. 2006, pp. 27–36.
11. W. Landi, "Undecidability of static analysis," ACM Letters on Programming Languages and Systems, vol. 1, no. 4, pp. 323–337, 1992.
12. N. L. de Poel, "Automated security review of PHP web applications with static code analysis and Data mining," M.S. thesis, State University of Groningen, May 2010.